Model-Data Fusion
Remote sensing in agroecosystem modelling

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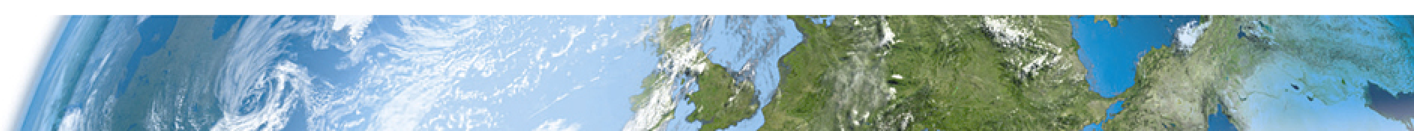
DLR

Agroecosystem models (Soil-Vegetation-Atmosphere Transfer (SVAT) models)

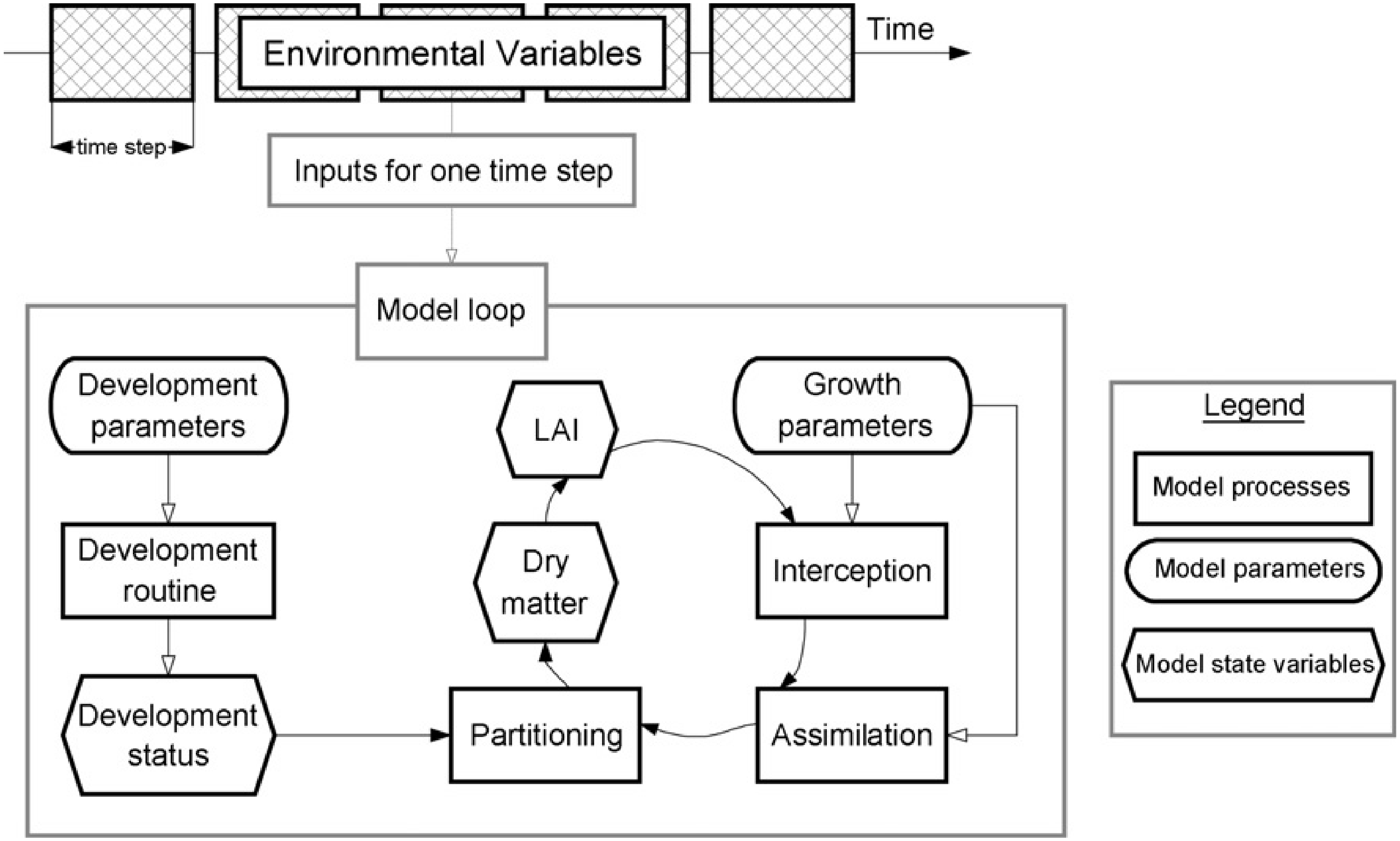
- simulate crop growth under different environmental and management conditions
- diagnose crop growing conditions
- predict crop yield (or accumulated biomass)
- help to understand crop behaviour
- help to design monitoring tools over large area
- assist in best (sustained) management practices for food security
- help to develop management strategies to minimize the impact of climate change



SVAT models

- use in-situ data (local representativeness)
- force to apply approximations and simplifications
- introduce various limiting factors as e.g. soil, weather, water, nitrogen
- operate in a dynamic way

SVAT models - simplified scheme of an agrosystem



Dorigo, et al. 2007

SVAT models

- use in-situ data (local representativeness)
- force to apply approximations and simplifications
- introduce various limiting factors as e.g. soil, weather, water, nitrogen
- operate in a dynamic way

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lack of precision, spatial uncertainty

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- influence simulation of two important physiological processes:
- crop canopy development
- soil moisture content

De Wit et al. 2007

Uncertainty in SVAT models

How to cope with?

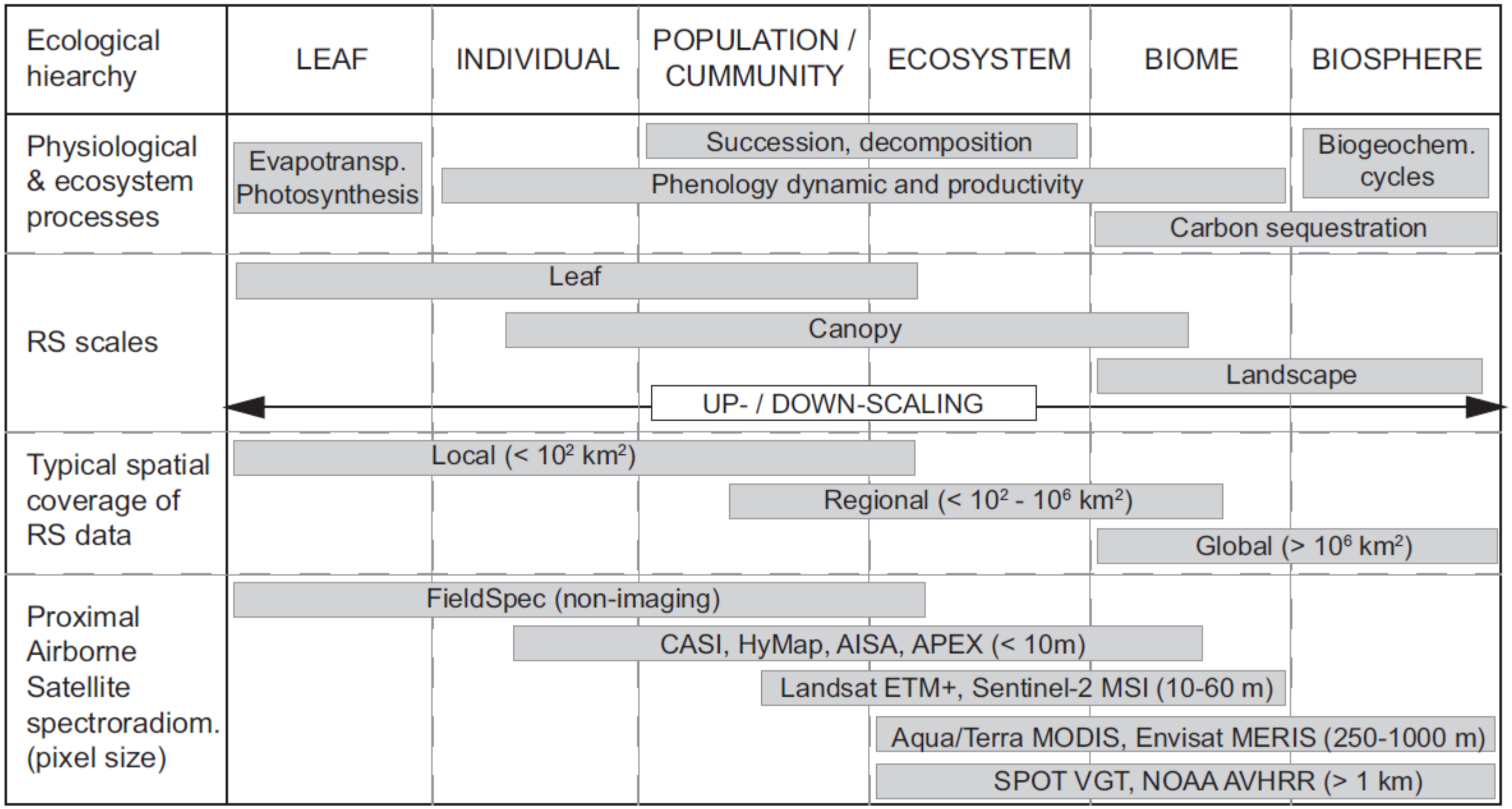
either… model run with default values for many variables

- \> disregarding spatial heterogenity
- \> introducing uncertainties

or… use of RS data

- \> provision of information on meteorological, vegetation, (e.g.phenological), and soil conditions over large areas
- \> introducing uncertainties…

Optical RS



Homolova et al. 2013

Optical RS

In the wavelength between 400 and 2500 nm the radiance of the vegetation canopy measured by the sensor is influenced by:

- optical properties of the vegetation elements themselves (leaves, stems, etc)
- arrangement of these elements in the canopy
- optical properties of the undergrowth and soil

- constellation of sensor parameters (viewing and illumination angle)
- atmospheric conditions (e.g. turbidity, aerosols)

Optical RS
- RS-derived state and driving variables, used in SVAT modelling

Biophysical parameter	Main indicator	Application	State (S) or driving (D)
Fraction of absorbed photosynthetically absorbed radiation (fAPAR)	Photosynthesis	Clevers (1997); Gobron et al. (2000)	S
Leaf Area Index (LAI)	Plant functioning	Bouman (1995); Doraiswamy et al. (2004); Mo et al. (2005); Moulin et al. (2003)	S
Fractional cover (fCOVER)	Plant development	Bouman (1995)	S
Chlorophyll and other pigments	Nitrogen stress/photosynthesis	Haboudane et al. (2002); Zhao et al. (2004)	S
Mineral content (K, P, Ca, Mg)	Crop quality	Mutanga et al. (2004)	S
Plant water content	Drought stress	Moran et al. (1994)	S
Above ground biomass/net primary production	Carbon storage; crop yield	Tucker et al. (1983)	S/D
Evapotranspiration	Drought stress	Bastiaanssen and Ali (2003); Hurtado et al. (1994)	D
Vegetation height	Plant development	Richardson et al. (1982)	S

Dorigo, et al. 2007

Integration of RS data in SVAT models

Statistical/ empirical approach

- > search for statistical relationship between the spectral signature and measured biophysical or biochemical properties of the canopy

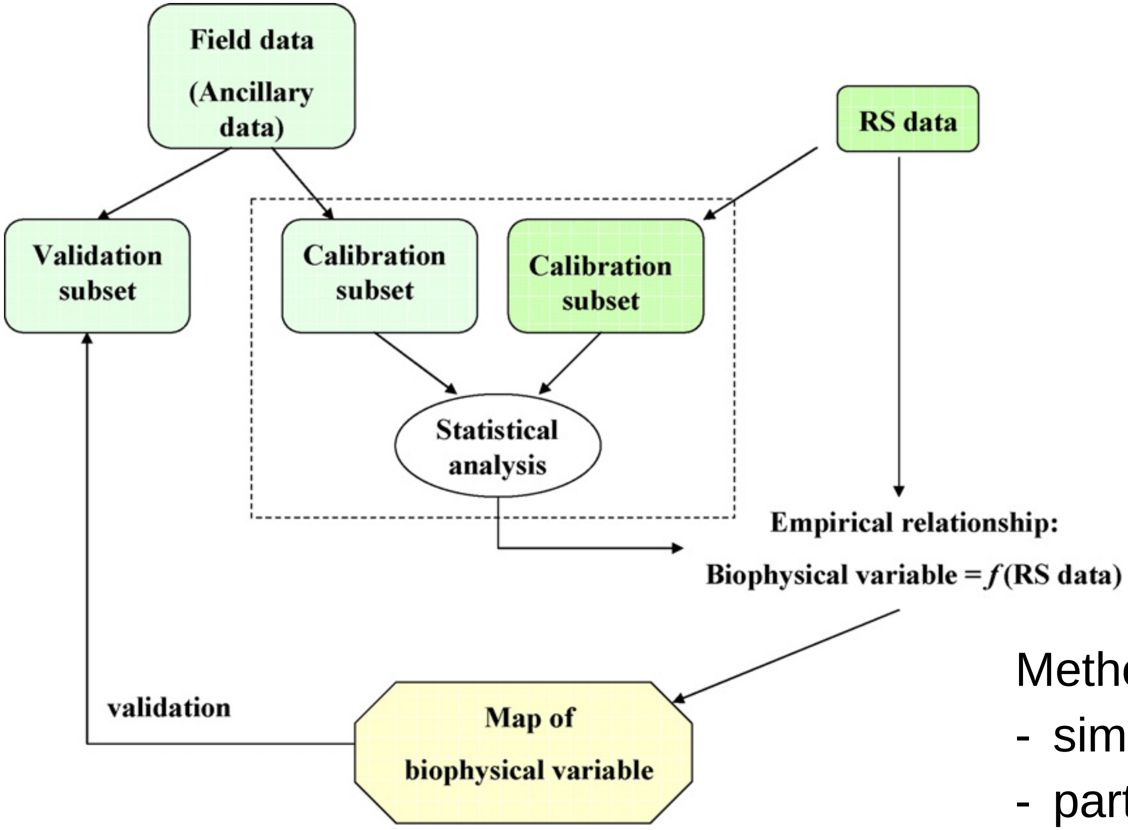
Physical approach

- > based on the radiation propagation within canopy

Hybrid approach

- > use of physical models to establish statistical relationship between the spectral signal and the biophysical parameters

Integration of RS data in SVAT models - statistical approach -



Methods:
- simple or multiple regression
- partial least square regression (PLS)
- artificial neural networks (ANN)

Dorigo, et al. 2007

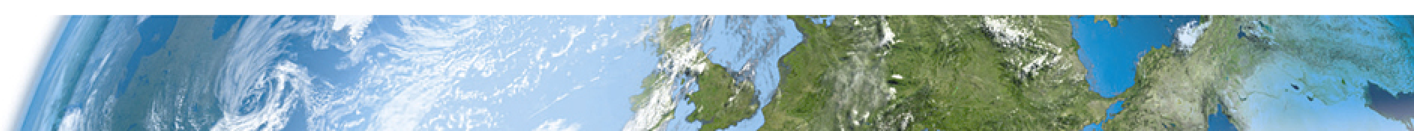
Integration of RS data in SVAT models - statistical approach - VIs

- > uses Vegetation Indices (VIs) to reduce background effects and enhance spectral features:

1. Broadband VIs (for multispectral sensors)
   a) Ratio VIs (e.g. NDVI)
   b) Orthogonal and hybrid VIs (e.g. SAVI)

2. Discrete narrow bands VIs (for hyperspectral sensors)
   a) Narrow band ratios
   (e.g. CARI – Chlorophyll Absorption Ratio Index, TVI - Triangular VI)
   b) Spectral shape and the red edge VIs
   (focused on the REIP – position of the Red-Edge- Inflection Point)
   c) Spectral continuum measures VIs
   (e.g. CACI – Chlorophyll Absorption Continuum Index)

Dorigo, et al. 2007



Integration of RS data in SVAT models - statistical approach - VIs

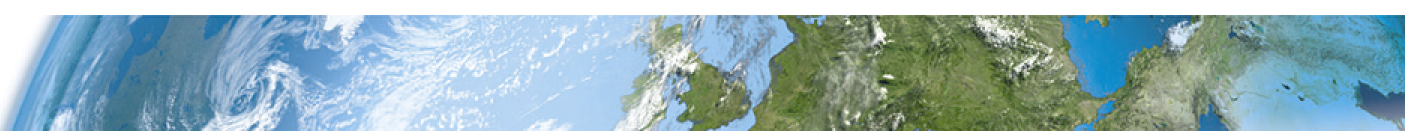
- by far the most widely used vegetation index is Normalized Difference Vegetation Index (NDVI)

- NDVI is used for e.g. for monitoring the continental or global scale with AVHRR- or MODIS-Data applications

- NDVI = $(\rho_{NIR} - \rho_{red}) / (\rho_{NIR} + \rho_{red})$

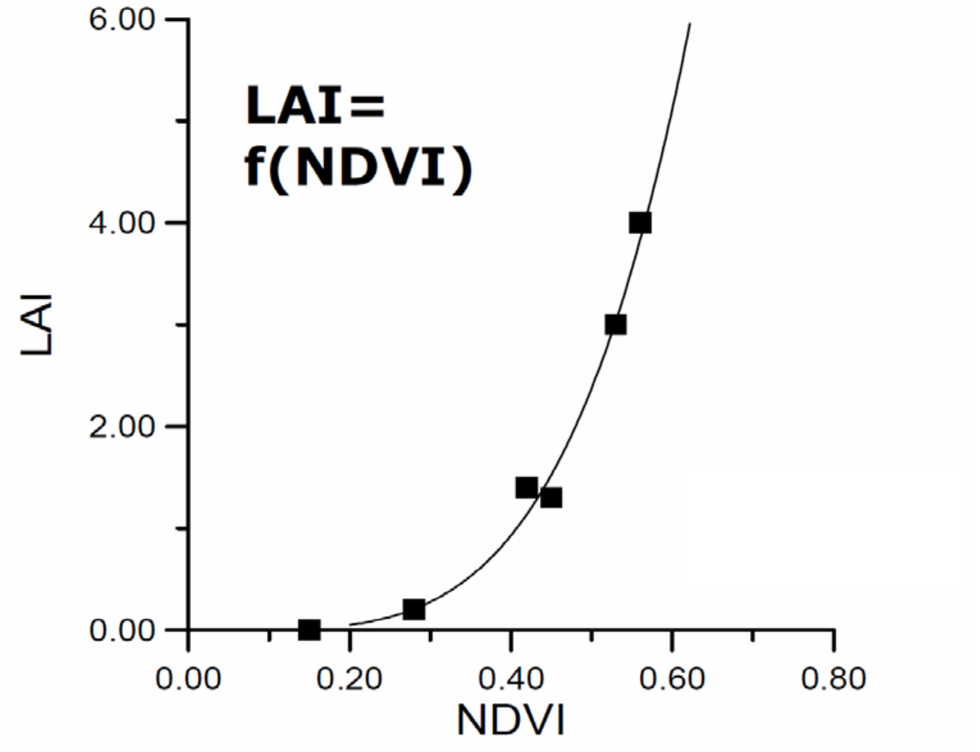
- NDVI generates a normalized values range between +1 and -1

	ρ_{rot}	ρ_{nIR}	NDVI
Wasser	2	0.2	- 0.82
Boden	8	13	0.37
Vegetation	4	45	0.84
heller Kalk	25	45	0.29
20 % Vegetation auf hellem Kalk	20.8	45	0.37



Integration of RS data in SVAT models - statistical approach - VIs

Example of relationship between NDVI and LAI



Lacaze et al. 1996

Integration of RS data in SVAT models - physical approach -

- > consists of inverting a canopy reflectance model for the estimation of leaf and canopy properties

- > simulate the interactions between solar radiation and the elements constituting the canopy using physical laws

- > combine a leaf optical model with a canopy reflectance and a soil reflectance model and calculate the top-of-canopy reflectance.

Integration of RS data in SVAT models - physical approach -

Examples of leaf and canopy reflectance models

Medium	Type	Leaf model	Canopy model
Homogeneous	1D radiative transfer	(Fukshansky et al., 1991)	SAIL (Verhoef, 1984), KUUSK (Kuusk, 1995a)
	Plate model	PROSPECT (Jacquemoud and Baret, 1990)	–
Heterogeneous	3D radiative transfer	–	DISORD (Myneni et al., 1992)
	Geometric	–	Chen and Leblanc (1997)
	Hybrid	–	DART (Gastellu-Etchegorry et al., 1996), GeoSAIL (Huemmrich, 2001), TRIM (Goel and Grier, 1988) INFORM (Schlerf and Atzberger, 2006)
	Ray tracing	RAYTRAN (Govaerts et al., 1996)	RAYTRAN (Govaerts and Verstraete, 1998), SPRINT (Goel and Thompson, 2000)
	Radiosity	ABM (Baranoski and Rokne, 1997)	PARCINOPY (Chelle and Andrieu, 1998)
	Stochastic	SLOP (Maier et al., 1999)	SMRT (Shabanov et al., 2000)

Dorigo, et al. 2007

Integration of RS data in SVAT models - physical approach -

Inversion of canopy reflectance models:

- > consists in finding the set of input parameters for the best match between the bi-directional reflectance factor (BRF) simulated with a canopy reflectance model and reflectance measured by the sensor

Methods:

- > Iterative optimization (e.g. Quasi-Newton algorithm, genetic algorithms, or Markov-Chain Monte Carlo approach)
- > Lookup tables (LUT)
- > ANNs

Integration of RS data in SVAT models
- statistical *vs* physical approach -

Statistical	Physical
Many field or laboratory measurements required for establishment of statistical relationship	Field or laboratory measurements only used for validation
Spectral data usually transformed	Original spectra used for inversion
Function usually based on a limited number of spectral bands	Inversion usually based on complete spectral information
Statistical function accounts for one variable at the time	Various parameters estimated at the same time
Not possible to incorporate information of other variables	Possibility to incorporate prior information on distribution of different variables
Computationally not very demanding	Computationally very intensive
Atmosphere, view, and sun geometry are not directly accounted for	Influences of atmosphere, view and sun geometry are directly incorporated
Statistical approaches normally based on nadir measurements	Possibility to use multiangular information
Little knowledge of user required	Knowledge of user required for the choice of appropriate canopy reflectance model, inversion technique, and distribution of variables

Dorigo, et al. 2007

RS data assimilation strategies in SVAT models

Data assimilation allows solid coupling of physical models, linking agroecosystem models to state space estimation algorithms

Within data assimilation framework:

1. Driving variables – force the system
2. State variables – provide a complete description of system behaviour
3. Model parameters – characterise the relationship between state- and driving variables
4. Output variables

(Schaepman et al. 2007, Dorigo et al. 2007)

RS data assimilation strategies in SVAT models

RS data available throughout growing season enable:

- **calibration** of the model – model parameters or initial states are adjusted to obtain an optimal agreement between the simulated and the observed state variables; re-estimation of the missing parameters

- **forcing** – replacement of a state variable in the model using the observed data; direct use of RS-derived parameter as a model input

- **updating** – consists of the continuously updating of model state variables, whenever an observation is available; based on the assumption that a better simulated state variable at day *t* will also improve the accuracy of the simulated state variable at day *t+1*; flexible in combining models

(Schaepman et al. 2007, Dorigo et al. 2007)

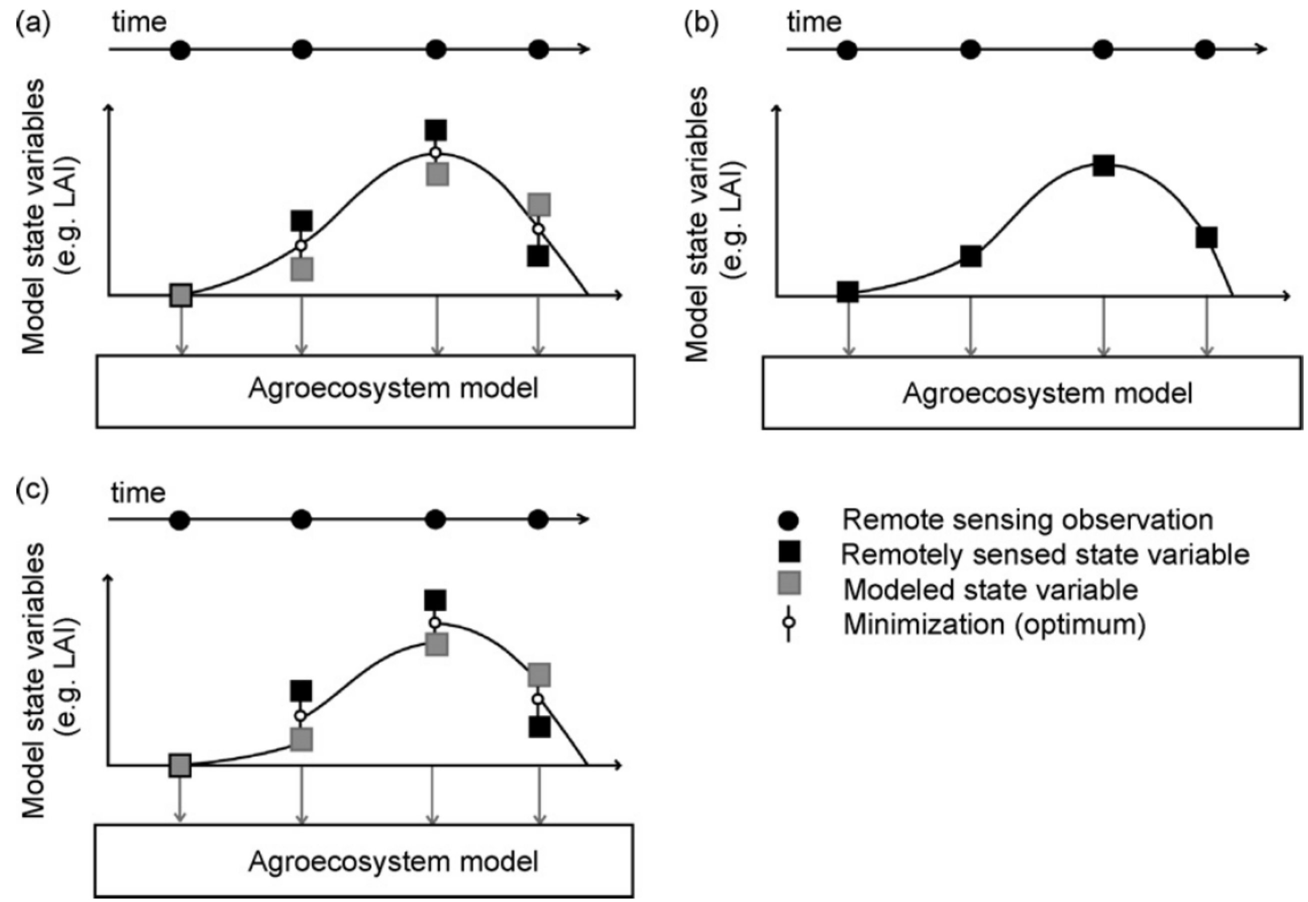
RS data assimilation strategies in SVAT models

Different RS assimilation methods

calibration

forcing

updating



(Dorigo et al. 2007, adapted from Delecolle et al. 1992)

RS data assimilation in SVAT models - model calibration

Procedure example I:

1. coupling a radiative transfer model to crop model through a canopy structure variable e.g. LAI)
2. simulation of RS variables (e.g. reflectance in NIR) for all dates with acquired RS data
3. comparison of simulated vs measured variables
4. re-estimation of some initial model parameters

accuracy of simulated state variables increase

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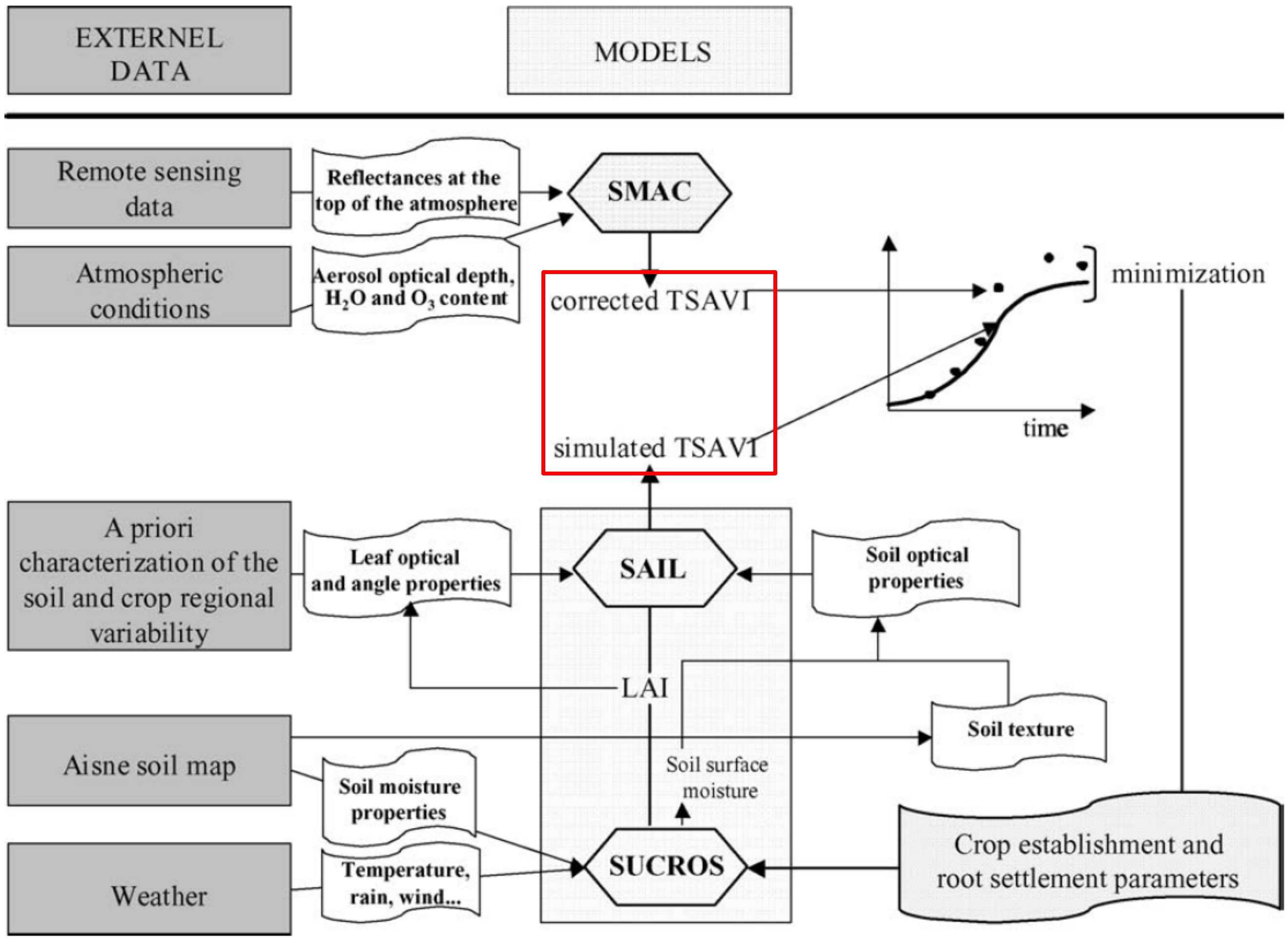
improved yield estimation

optimization ~ data assimilation

(Launay and Guerif 2005)

RS data assimilation in SVAT models
- model calibration -

Example II:



(Launay and Guerif 2005)

RS data assimilation in SVAT models - model updating -

Example of methods to combine the modelled and the observed state variables:

- > Newtonian nudging algorithm
- > various types of Kalman filters

quantify the relative weight that should be assigned to the modeled and observed state variables

(Dorigo et al. 2007, adapted from Delecolle et al. 1992)

RS data assimilation strategies in SVAT models - Kalman filter

- also known as linear quadratic estimation (LQE)
- co-invented and developed by Rudolf Emil Kálmán in the early 1960s
- the first implementation in trajectory estimation for the Apollo program of the NASA Ames Research Center (incorporation of Kalman filter in the Apollo navigation computer)
- sequential data assimilation method
- model is integrated forward in time
- whenever measurements are available, these are used to reinitialize the model before the integration continues

RS data assimilation strategies in SVAT models - Kalman filter

Given a linear dynamical model written on discrete form as: $\psi_{k+1} = \boldsymbol{F}\psi_k$

the error covariance equation as: $\boldsymbol{P}_{k+1} = \boldsymbol{F}\boldsymbol{P}_k\boldsymbol{F}^T + \boldsymbol{Q}$

Model forecast ψ^f, analyse ψ^a and measurements d:

$$\psi^a = \psi^f + \boldsymbol{P}^f\boldsymbol{H}^T(\boldsymbol{H}\boldsymbol{P}^f\boldsymbol{H}^T + \boldsymbol{R})^{-1}(\boldsymbol{d} - \boldsymbol{H}\psi^f)$$

Covariances for model forecast P^f, analyse P^a and measurements R:

$$\boldsymbol{P}^a = \boldsymbol{P}^f - \boldsymbol{P}^f\boldsymbol{H}^T(\boldsymbol{H}\boldsymbol{P}^f\boldsymbol{H}^T + \boldsymbol{R})^{-1}\boldsymbol{H}\boldsymbol{P}^f$$

where H is measurement operator of observation $\boldsymbol{d} = \boldsymbol{H}\psi^t + \epsilon$

(Evensen 2003)

RS data assimilation strategies in SVAT models - Kalman filter

weights are determined by the

- error covariance for the model prediction projected onto the measurements,
- the measurement error covariance, and
- the difference between the prediction and measurements (innovation)

Derivation of Kalman Filter - > so-called Kalman gain matrix

$$\boldsymbol{K} = \boldsymbol{P}^f \boldsymbol{H}^T (\boldsymbol{H}\boldsymbol{P}^f \boldsymbol{H}^T + \boldsymbol{R})^{-1}.$$

Some developments of Kalman filters:

The Extended Kalman Filter (EKF)
The Ensemble Kalman Filter (EnKF)
…

(Evensen 2003)

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Thank you for listening!

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